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Development of an Information Fusion System for Engine Diagnostics and Health Management

Allan J. Volponi
Pratt & Whitney, East Hartford, Connecticut

Tom Brotherton
Intelligent Automation Corporation, Poway, California

Robert Luppold
Luppold & Associates, West Newton, Pennsylvania

Donald L. Simon
U.S. Army Research Laboratory, Glenn Research Center, Cleveland, Ohio

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Allan J. Volponi, Tom Brotherton, Robert Luppold, and Donald L. Simon

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John H. Glenn Research Center at Lewis Field
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Aircraft gas-turbine engine data are available from a variety of sources including on-board sensor measurements, maintenance histories, and component models. An ultimate goal of Propulsion Health Management (PHM) is to maximize the amount of meaningful information that can be extracted from disparate data sources to obtain comprehensive diagnostic and prognostic knowledge regarding the health of the engine. Data Fusion is the integration of data or information from multiple sources, to achieve improved accuracy and more specific inferences than can be obtained from the use of a single sensor alone. The basic tenet underlying the data/information fusion concept is to leverage all available information to enhance diagnostic visibility, increase diagnostic reliability and reduce the number of diagnostic false alarms. This paper describes a basic PHM Data Fusion architecture being developed in alignment with the NASA C17 Propulsion Health Management (PHM) Flight Test program. The challenge of how to maximize the meaningful information extracted from disparate data sources to obtain enhanced diagnostic and prognostic information regarding the health and condition of the engine is the primary goal of this endeavor. To address this challenge, NASA Glenn Research Center (GRC), NASA Dryden Flight Research Center (DFRC) and Pratt & Whitney (P&W) have formed a team with several small innovative technology companies to plan and conduct a research project in the area of data fusion as applied to PHM. Methodologies being developed and evaluated have been drawn from a wide range of areas including artificial intelligence, pattern recognition, statistical estimation, and fuzzy logic. This paper will provide a broad overview of this work, discuss some of the methodologies employed and give some illustrative examples.

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APPENDIX

Table A: Examples of Parameter Measurement Information for Data Fusion

Parameter	Sample Rate (Hz)	Engr. Units
Aircraft		
Mach No.	25	
Pressure Altitude	25	FT
Calibrated Airspeed	25	KNOTS
True Airspeed	25	KNOTS
Indicated Airspeed	25	KNOTS
Angle of Attack	50	DEG
Alpha Dot, (AOA Rate)	6	DPS
Roll Angle	50	FPS
Pitch Angle	50	FPS
Heading Angle	50	DEG
Roll Rate	50	DPS
Pitch Rate	50	DPS
Yaw Rate	50	DPS
Flight Path Angle	50	DEG
Altitude Rate	25	FPM
Total Temperature	10	Deg C
Total Pressure	25	IN HG
Static Temperature	10	Deg C
Static Pressure	25	IN HG
Commands		
High Press. Compressor Variable Vane Position	5	Inches
Station 2.5 Bleed Valve Position	5	% Open
Thrust Lever Angle	20	Degrees
High Pressure Turbine Clearance Valve Position	5	% Open
Low Pressure Turbine Clearance Valve Position	5	% Open
Air / Oil Heat Exchanger Valve Position	5	% Open
Oil/Fuel System		
Oil Quantity	2.5	Quarts
Fuel Temperature at Fuel/Oil Heat Exchanger	5	Deg C
Main Oil Temperature	5	Deg C
Main Oil Differential Pressure	5	PSIG
# 4 Bearing Compartment Exit Pressure	2.5	PSIG
Fuel Pump Exit Pressure	20	PSIA
#1, 2, 3 Bearing Compartment Exit Temperature	20	Deg C

Parameter	Sample Rate (Hz)	Engr. Units
Gas Path		
N1	20	% RPM
N2	20	% RPM
Burner Static Pressure	5	PSIA
High Pressure Compressor Exit Total Temperature	5	Deg C
EGT Total Temperature	20	Deg C
Engine Inlet Total Temperature	5	Deg C
Engine Inlet Total Pressure	5	PSIA
Low Pressure Turbine Exit Total Pressure	5	PSIA
Fuel Flow	5	PPH
Low Pressure Compressor Exit Total Temperature	20	Deg C
Low Pressure Compressor Exit Total Pressure	20	PSIA
Structural Assessment Sensors		
Stewart Hughes IDMS Sensor # 1	12.5K	VDC
Stewart Hughes IDMS Sensor #2	12.5K	VDC
Stewart Hughes EDMS Sensor	12.5K	VDC
SwanTech Sensor #1 (Inlet Stator)	23.15K	VDC
SwanTech Sensor #2 (E-Flange)	23.15K	VDC
SwanTech Sensor #3 (Gearbox)	23.15K	VDC
SwanTech Sensor #4 (K-Flange)	23.15K	VDC
SwanTech Sensor #5 (#5 Bearing Oil Pressure)	23.15K	VDC
B-Flange High Frequency Acceleration	46.3K	g
B-Flange Low Frequency Acceleration	5.8K	g
P-Flange High Frequency Acceleration	23.15K	g
P-Flange Low Frequency Acceleration	5.8K	g
Gearbox High Frequency Acceleration	46.3K	g
Gearbox Channel 1 (X-axis Acceleration)	23.15K	g
Gearbox Channel 2 (Y-axis Acceleration)	23.15K	g
Gearbox Channel 3 (Z-axis Acceleration)	23.15K	g

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DEVELOPMENT OF AN INFORMATION FUSION SYSTEM FOR ENGINE DIAGNOSTICS AND HEALTH MANAGEMENT

Allan J. Volponi
Pratt & Whitney
East Hartford, Connecticut 06108

Tom Brotherton
Intelligent Automation Corporation
Poway, California 92064

Robert Luppold
Luppold & Associates
West Newton, Pennsylvania 15089

Donald L. Simon
U.S. Army Research Laboratory
Glenn Research Center
Cleveland, Ohio 44135

ABSTRACT

Aircraft gas-turbine engine data are available from a variety of sources including on-board sensor measurements, maintenance histories, and component models. An ultimate goal of Propulsion Health Management (PHM) is to maximize the amount of meaningful information that can be extracted from disparate data sources to obtain comprehensive diagnostic and prognostic knowledge regarding the health of the engine. Data Fusion is the integration of data or information from multiple sources, to achieve improved accuracy and more specific inferences than can be obtained from the use of a single sensor alone. The basic tenet underlying the data/information fusion concept is to leverage all available information to enhance diagnostic visibility, increase diagnostic reliability and reduce the number of diagnostic false alarms.

This paper describes a basic PHM Data Fusion architecture being developed in alignment with the NASA C17 Propulsion Health Management (PHM) Flight Test program. The challenge of how to maximize the meaningful information extracted from disparate data sources to obtain enhanced diagnostic and prognostic information regarding the health and condition of the engine is the primary goal of this endeavor. To address this challenge, NASA Glenn Research Center (GRC), NASA Dryden Flight Research Center (DFRC) and Pratt & Whitney (P&W) have formed a team with several small innovative technology companies to plan and conduct a research project in the area of data fusion as applied to PHM.[1] Methodologies being developed and evaluated have been drawn from a wide range of areas including artificial intelligence, pattern recognition, statistical estimation, and fuzzy logic. This paper will provide a broad overview of this work, discuss some of the methodologies employed and give some illustrative examples.

INTRODUCTION

Reliable engine performance diagnostic methods have become an important factor in reducing the total cost of ownership of gas turbine engines. A pivotal requirement for successful diagnostics is the ability to detect and isolate engine system faults in a timely manner. To address this issue, the gas turbine industry has begun to focus on the development of intelligent engine health monitoring (EHM) systems. In the context of EHM systems, intelligence implies the ability to detect and isolate faults to a line replaceable unit (LRU) (diagnostics) as well as the ability to determine when maintenance should be performed (prognostics). One approach to achieving this level of intelligence involves the use of information fusion concepts. The net effect of such a system would be to increase diagnostic reliability, capability and coverage, decrease diagnostic *false alarms,* and support expandability and adaptability to new information sources.
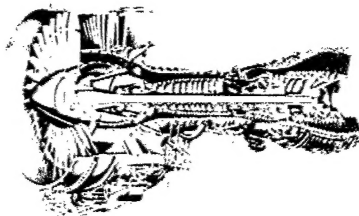

In this paper we shall describe a general architecture for information fusion as applied to aero-engines for the purpose of supporting engine diagnostics and prognostics. The general structure is adaptable in the sense that it can be expanded or contracted to fit the specific engine configuration and data infrastructure. Specific elements of the system will be described in terms of an example system being developed under a joint NASA GRC and DFRC research program on the C17-T1 aircraft.

C17 Globemaster

DIAGNOSTICS AND INFORMATION FUSION

The subject system described in this paper is a collaborative effort between NASA Glenn and Dryden Research Centers, Pratt & Whitney and several technology companies, and is closely aligned with a NASA C-17 Propulsion Health Management (PHM) Flight Test Program for the P&W F117 engine powering the C17-T1 military transport. The C-17 PHM Flight Test Program is flight testing a variety of sensors, and developing signal processing, analysis modules, and a high level reasoner for fault isolation. A general architecture for incorporating these elements has been defined and will be discussed in the sequel.

Pratt & Whitney F117 Engine

Before exploring the diagnostic fusion architecture, we should consider the possible sources of data and information that could potentially feed the process. To achieve the goal of increasing diagnostic capability and reliability, the system takes advantage of a number of technology elements, such as Signal Processing methods, Physics-based Models, Empirical Models, and High Level Reasoners to combine all of the information. The general architecture for implementing this strategy accommodates a wide range of engine sensors covering high and low bandwidth signals, including, but not limited to, aircraft, gas path, lubrication system, and structural indicators as well as special application engine health sensors. Some examples of these types of sensor measurements are described below.

POTENTIAL DATA / INFORMATION SOURCES

Engine Gas Path Measurements
These consist of some subset of inter-stage pressures and temperatures, spool speeds, fuel flow, etc. Depending on the engine type this can range from four flight parameters up to as many as 12. In addition, measurements such as inlet temperature, pressure, Mach No. and altitude define the flight condition and aid in the normalization of the main gas path parameters.

Oil / Fuel System Measurements
These consist of various oil system temperatures, pressures, fuel temperature and delivery pressure. Advanced sensors indicating oil quality and oil debris monitoring sensors as well as oil quantity measurements may be available.

Vibration Measurements
Some form of vibration monitoring is typically performed on most engines. This is usually on the low spool to measure Fan and Low Pressure Turbine (LPT) vibration, but may include high spool vibration probes as well as specific bearing and gearbox vibration measurements.

Structural Assessment Sensors
These sensors aid in assessing structural integrity of the engine. Examples include Inlet and Exhaust debris monitors, acoustic sensors, high bandwidth vibration sensors, multi-axis vibration, and blade tip clearance monitors.

FADEC Codes
The electronic engine control performs a myriad of performance tests on signal condition and fidelity. Cross channel checks can aid in determining whether or not a main engine sensor is drifting, going out of limit, or failing. Checks on bleed valves, active clearance control, and variable geometry can provide independent information regarding engine health and the health of various engine subsystems.

Onboard Engine Models
Accurate engine models embedded within the FADEC or residing within a dedicated PHM hardware unit can be used to generate virtual engine measurements to aid in detecting faulty engine instrumentation or confirming degraded engine performance. Self Tuning Onboard Real Time Models (STORM) have been developed for this purpose [1]. These models adapt themselves to changing conditions observed in the engine's measurement suite and can be used to estimate engine module degradation as well as to provide a suite of *virtual sensors*.

Maintenance/Analysis History
Information regarding the performance disposition of the major modules that comprise the engine can potentially be used as *a-priori* information to support the identification and estimation of performance changes within a Module Performance Analysis (MPA) program. Similarly, knowledge of past maintenance actions and past analysis results may also be used to aid in differentiating between engine component performance faults and engine controls and accessories malfunctions, such as bleed leaks, cooling problems, and similar problems.

Companion Engine Data
On multi-engine aircraft, information from the companion engines might be used to provide additional independent confirmation of instrumentation problems and engine events.

Negative Information

This pertains to a reasoning methodology more than an actual source of information. Negative information constitutes conditions that were not present but would or should have been perceived under the hypothesis that a certain fault scenario exists. In mathematical parlance, it is referred to as *proof by contradiction*. For example, if Active Clearance Control (ACC) were not enabled (i.e. a faulty operation) then Exhaust Gas Temperature (EGT) should increase. If EGT was not observed to increase, then the original assumption is probably false, i.e. ACC must be working properly. This type of *information* would best be employed in an expert system-like structure, which governs the overall analysis and processing of the engine data.

POTENTIAL DATA / INFORMATION FUSION APPROACHES

With such a wealth of potential information, one must decide in what manner to combine or *fuse* information for the stated diagnostic goal. In general, data can be *fused* at different *levels*, [2], for example:

> ➤ *sensor level* fusion where multiple sensors measuring correlated parameters (e.g. oil pressures, exhaust gas temperatures, etc.) can be combined.

> ➤ *feature level* fusion, where analysis information (e.g. component performance changes, event detection) resulting from independent analysis methods can be combined.

> ➤ *decision level* fusion, where diagnostic actions (e.g. damage assessments, maintenance advisories) can be combined.

The level of fusion that is appropriate will, in general, depend on many factors including available sensors, models, analysis algorithms, data monitoring and recording specifics (continuous vs. discrete data), computing platform, etc. In the case of engine diagnostics, it might be argued that different levels of information fusion will be required depending on whether the system is for a military or a commercial application. In military applications, dedicated Propulsion Health Management (PHM) systems utilizing independent engine monitoring and analysis hardware and/or direct FADEC involvement is not uncommon. In these scenarios, data are collected and analyzed in real time onboard the aircraft during flight. In commercial applications much of the data collected are discrete in nature (several data points per flight, typically at takeoff and cruise). This information is downloaded to ground-based computer systems for subsequent analysis and trending. It is also more likely that *advanced* sensors are used in the military environment (as in the C17 T1 program) than in commercial applications, where the historical trend is to minimize sensors and data collection hardware.

In order to provide the most generic and expandable system which can be applied to a wide variety of engine applications with varied instrumentation and data sources, we have chosen to perform the information fusion at the feature level. The general architecture is depicted in Figure 1. This scheme provides for the potential inclusion of a variety of sensors, standard, special, low frequency and high frequency as well as other pieces of diagnostic relevant information that might be in the form of fault codes, maintenance records, and observations. The general structure provides for information synchronization to align the data to a common timeframe, analysis modules for salient feature extraction, and high-level fusion [3].

Figure 1 below, depicts a general configuration for an engine diagnostic/prognostic system incorporating the elements of information fusion discussed above. A specific PHM system incorporating data fusion may have some but not all of these elements depending on the type, quantity, and availability of sensors, models, and analysis methods. The general architecture does not address the specific nature of models and analysis or their interdependencies except to acknowledge that they exist and provide placeholders for them.

Figure 1: General PHM Information Fusion Architecture

For a particular application there are a myriad of design and implementation issues that need to be resolved and defined. They include but are not necessarily limited to the following:

1. Data Acquisition
   - Signal types (continuous vs. discrete)
   - Signal sampling rates
   - Signal synchronization across suite of sensors
   - Signal conditioning / processing

2. Data Processing
   - On-board Processing

- Hardware capabilities/constraints
- Processing bandwidth
- Storage requirements
- Reporting / Fault annunciation
- Off-board Processing (if any)
- Data communication infrastructure

3. Model / Analysis Algorithm Development
   - Physics-based model development specific to engine system/subsystem
   - Empirical model development
   - Interdependency between models and analysis algorithms
   - Development of expert system control program
   - Prognostic and Health reasoning systems

Data analysis tools are required to reduce, analyze and interpret the information collected. This will generally consist of algorithms employing some form of modeling (either physics-based or empirical), along with attendant data reduction and fault detection, isolation and estimation algorithms specific to the type of data collected and engine system/sub-system being analyzed. The specific methodologies that might be employed in such an effort will be highly dependent on the particular data/information being collected. It should also be evident that there exists an implicit interdependency between the data available and the analysis algorithm as well as an interdependency between an analysis algorithm and the level of modeling available.

As an example, Gas Path Analysis (GPA), which will be described later in the paper, utilizes a set of gas path measurements taken together to collectively assess changes in a set of module performance parameters. This type of analysis requires the use of physics-based models to represent the reference level from which a comparison is to be made in order to estimate changes in performance from that reference level. This defines a dependency between model and method. Likewise, the algorithms typically employed to estimate these performance changes have a predictor/corrector structure in that *a-priori* knowledge of the type of fault encountered will directly impact the estimator's ability to accurately assess the fault level. Thus, if our sensor suite includes an electro-static inlet debris monitor, for example, then having a positive (debris ingestion) annunciation would indicate a FOD event that would allow a focusing of the estimation algorithm to those Modules most likely affected, thus increasing the likelihood of correctly detecting and isolating the fault. Thus there can be an interdependency between data/information and the analysis algorithm.

The general architecture incorporates several modules that provide signal processing and conditioning, and engine health feature extraction through the use of physics-based and empirical model analysis. It also uses a two tier high level fusion process wherein the engine health features are combined to form a comprehensive engine health assessment, using ancillary engine information from engine control fault codes, and maintainer and pilot observations, to provide a knowledge base for software directed maintenance. The functionality within these modules will be described below in terms of the specific C17-T1 PHM application alluded to at the beginning of this paper.

C17-T1 PHM APPLICATION

The NASA C17 PHM Flight Test program and the Data Fusion program are multi-year research initiatives focused on defining and flight-demonstrating integrated PHM system technologies suitable for civil and military aircraft application. The C17-T1 is powered by four Pratt & Whitney F117 turbofan engines. Engine #3 of the T1 aircraft has been instrumented beyond the typical Bill of Material (BOM) sensor suite with extensive gas path, oil system, vibration and structural assessment sensors, making it a prime candidate for information fusion research. In the following sections the elements of the C-17 T1 aircraft data fusion application

(see Figure 1) will be reviewed including instrumentation and data sources, modeling and algorithms, and high level fusion.

C17-T1 INSTRUMENTATION AND DATA SOURCES

Examples of the types of parameters available on this research airframe can be found in Table A in the Appendix.

A complete list can be found in [4]. In addition, a number of FADEC discrete data bits and flags for annunciating engine bleed, variable stator vane actuation, and health status are also available. Most of the sensors listed in Table A are common flight instrumentation and require no further explanation. The sensors listed under the category *structural assessment* are not so common and are undergoing flight evaluation on the T1 aircraft as part of the C-17 PHM Flight Test program. These advanced sensors are briefly described below.

The *Inlet Debris Monitoring Sensor* (IDMS) is mounted in the inlet forward of the FAN and monitors the electrostatic charge associated with debris ingested at the engine inlet. It is designed to detect the size, quantity, velocity, and to a limited extent composition of debris (i.e. damaging/non-damaging) entering the inlet.

The *Engine Distress Monitoring Sensor* (EDMS) is installed in the upper actuator housing of the thrust reverser casing. This sensor monitors the electrostatic charge of debris exiting the engine, which is likely to have been produced by engine distress. This system monitors the exhaust for changes in the level or nature of this debris. Normal healthy engine operation results in a small amount of erosion of various engine components that show up as fine particulate within the gas path. Changes in the nature or quantity of this exhaust debris have the potential for being an early warning of excessive wear or incipient failures.

The *Stress Wave Analysis Sensor* (SWAN) is a lightweight integrated circuit piezoelectric transducer that monitors structurally borne ultrasonic sound vibrations to measure the energy created by shock or friction events. It is an external sensor that requires a mount point that provides a mechanical sound path to the component being monitored. Five of them are mounted on the engine gearbox and flanges.

A set of 3 *High Frequency Vibration Sensors* (HFVS) are mounted on the engine. One is located on the gearbox, one on engine case flange B (forward), and one on flange P (aft). These sensors will allow the high frequency response of the components of the engine and gearbox to be tracked.

MODELING AND ALGORITHMS

Of equal importance, in a data fusion effort, as the data itself, is the repertoire of analysis tools required to reduce, analyze and interpret the information collected. For the application at hand, a set of specialized algorithms employing both physics-based and empirical methodologies has been employed. These include 1) data alignment for synchronizing the raw data/information to a common sample rate for subsequent analysis; 2) gas path anomaly detection which offers an empirical model of nominal gas path behavior with quantitative metrics for inferring the level of

departure from normal when applicable; 3) gas path analysis which provides for the isolation, estimation and tracking of engine Module performance faults; and 4) lubrication system modeling taking the form of empirically derived models for estimating oil quantify and bearing pressure. A brief synopsis regarding the nature of these algorithms is given below; a detailed description is beyond the scope of the present paper.

Data Alignment

As Table A indicates, the information being collected ranges dramatically in bandwidth from 2.5Hz to 50Hz for the low frequency sensors and from 5.8KHz to 46.3KHz for the high frequency sensors. Referring to the system architecture in Figure 1, the high frequency information will be processed by specialized algorithms in order to capture the salient information content of the signal and distilled to low bandwidth feature information at approximately 1Hz. As a precursor to eventual information fusion, these data along with the remaining low frequency sensor signals is time synchronized to a common sampling rate. For this application, the data alignment frequency is 20Hz and is accomplished by up and down sampling of the raw signal.

Gas Path Anomaly Detection

A PHM system generally has provisions for the detection and isolation of known fault conditions. During the course of engine operation, however, it is possible to encounter fault conditions or other off-nominal situations that were either never anticipated, never modeled or incorrectly modeled or never encountered in previous engine operation. Such events can be referred to as *anomalies* and it is prudent to provide for the detection of such occurrences [5,6].

To address unanticipated anomalies empirical models developed from a statistically significant sample of *nominal* engine operation data can be used to form the basis for an *anomaly detector*. These types of models typically take the form of Artificial Neural Networks (ANN) and are trained to output normal engine operation measurement estimates. When compared to actual measurements they provide a basis for making a statistical determination as to whether or not the observations at hand conform to what is considered "normal" operation. An empirical model of the *gas path* components is under development for the C17-T1 PHM system. The underlying modeling mechanism is a Radial Basis Function (RBF) ANN. During the training process for these types of ANNs, the training data is self-organized into a group of classes wherein each class is modeled by an n-dimensional Gaussian function referred to as a radial basis function. These functions capture the statistical properties and dimensional inter-relationships between the input and output engine data parameters. The structure an RBF ANN is depicted in Figure 2.
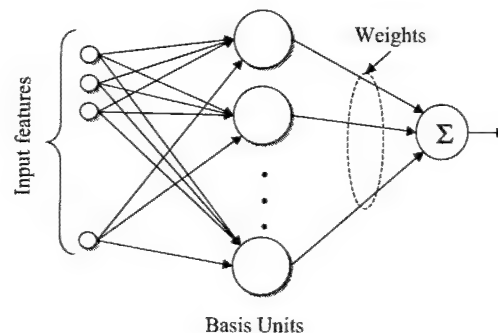

Figure 2: Radial Basis Function ANN

The Gas Path Anomaly Detector (AD) for the C17-T1 is configured as a set of several RBF ANNs, each representing a particular flight regime or operational characteristic to enhance the accuracy of the overall detector. For example there is an RBF ANN for steady state operation with and without stability bleed off-take, acceleration and deceleration. Simple regime recognition logic controls the selection of the appropriate RBF ANN. Pre-processing of engine parameters in

terms of standard day corrections and range normalization are made prior to input into the ANN. The primary output of the system is a (fuzzy-like) detection variable that takes on the values between 0 (*anomalous* data) and 1 (*normal* data). A threshold and median filtering is applied to the output to produce a discrete binary parameter to serve as a detection flag. A representation of this model is depicted in Figure 3, below.
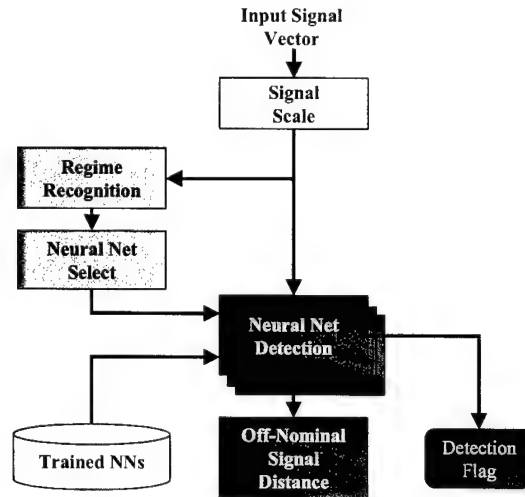

Figure3: Gas Path Anomaly Detector Model

In addition to the binary AD output parameter, individual input parameter *distance measures* are available which quantify each parameter's contribution to the data's classification as normal or anomalous. Collectively, these provide an empirical *signature* for anomalous data and are particularly helpful in determining in-range sensor faults. A graphical depiction of the output for a segment of an *actual* C17-T1 flight with a *simulated* Fuel Flow bias added (as an anomaly) is given in Figure 4.
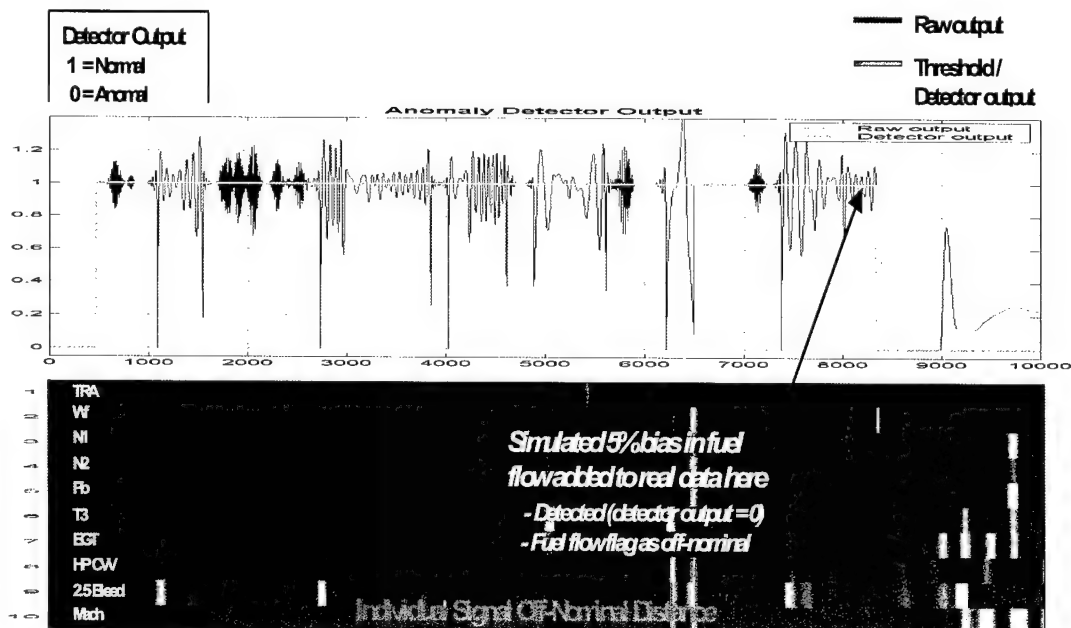

Figure 4: Graphical depiction of Gas Path Anomaly Detector output

The upper chart in Figure 4 portrays the raw output (blue) and the threshold (binary) output (orange) of the AD for nominal operation and an implanted (simulated) fuel flow fault. The lower chart is a color-coded graphical representation of the individual input parameter distance measures, where blue signifies normal and red signifies abnormal.

Gas Path Analysis

Traditional Gas Path Analysis provides for the isolation, estimation and tracking of engine Module performance faults. As a three decade old practice, it has been the subject of considerable research and a variety of methods have evolved using such disparate techniques such as optimal estimation, fuzzy logic, Neural Networks, Bayesian Belief Networks, and Kalman Filters. [7-14]. The efficacy of any of these methods depends on many factors and is somewhat application dependent, although they all share the same characteristic of assessing *change* in performance relative to some reference. In the context of the present application we have chosen a modified Kalman Filter approach with the frame of reference being the monitored engine at time of installation.

For the C17-T1 the reference level is obtained via a hybrid engine model consisting of a simple real-time physics based State Variable engine Model (SVM) coupled with an empirically determined modeling element to form a *hybrid* model representation of the monitored C17-T1 engine. The empirical element takes the form of a Multi-Layer Perceptron (MLP) Artificial Neural Network (ANN) that models the difference between the subject engine (at installation) and the SVM. The above elements, in combination with a Kalman Filter observer acting on the residuals between the hybrid model and the monitored engine, provides the requisite process for performing the gas path analysis. The configuration (in its most simplistic form) is given in Figure 5.
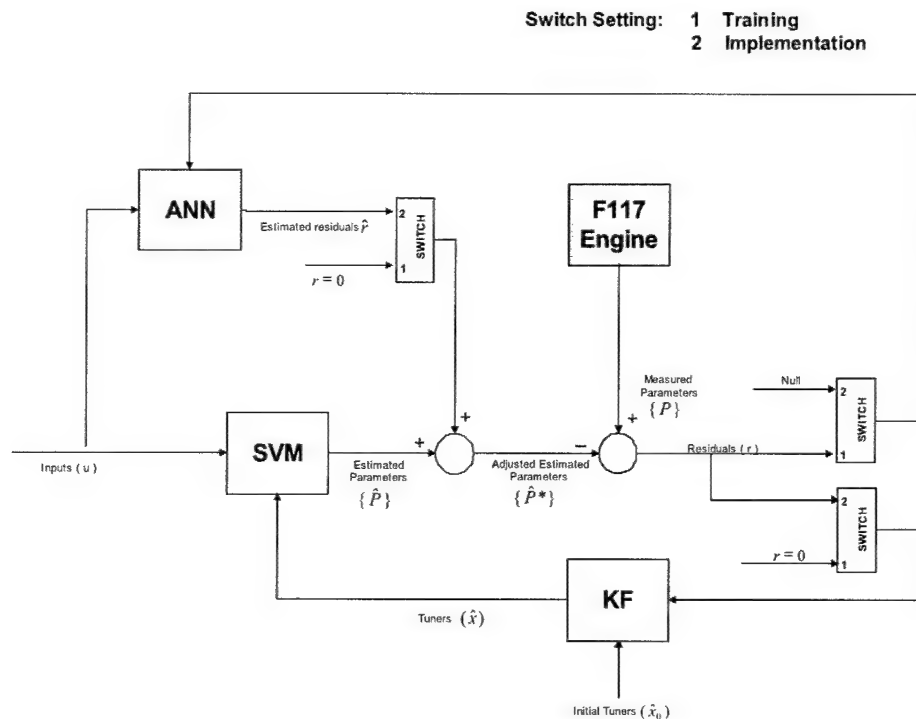

Figure 5: C17-T1 Hybrid Model Gas Path Analysis System

In Figure 5, the output from the Kalman Filter observer (KF) labeled *Tuners*, refers to a vector of module performance *changes* (from installation) which are estimated from the measurement residual input to the Kalman Filter. These Tuners are tracked over time for diagnostic purposes, and also fed back to the SVM to update the model measurement predictions which in the closed loop are forced to *match* the actual engine measurements (on the average), i.e. driving the residuals to zero. The empirical element (MLP ANN) in the hybrid representation is required to mitigate the effects (on the *Tuners*) of model inaccuracies and deficiencies. Figure 6 below illustrates this effect on the *Tuners* for actual C17-T1 engine data.
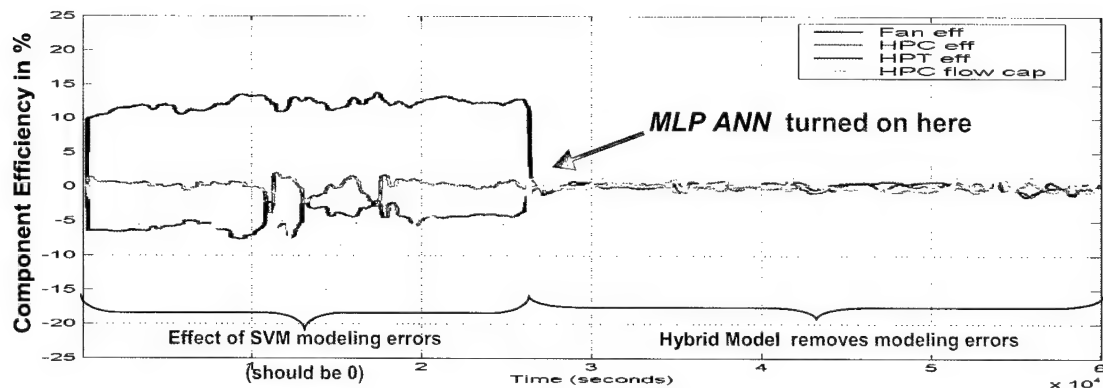

Figure 6: Establishing the Zero Reference for Module performance tracking

Once the reference level is established (zero on the average) for the Module performance deltas, only then can component deterioration be effectively tracked over time. For the interested reader, an introductory presentation of this methodology is given in [15].

Lubrication System Modeling

Initial work in this area has taken the form of empirically derived models for estimating Oil Quantity (POILQ) and number 4 bearing pressure (PN4SP) from other available engine oil system measurements (Main Oil Temperature and Pressure), gas path measurements, and other engine and flight parameters, a total of 14 input parameters (see Table 1 below).

Table 1: Input Parameters for Initial Empirical Lubrication Model

Parameter name	Description
ptfuel	Fuel Temperature at Fuel/Oil Heat Exchanger
ptoil	Main Oil Temperature
poilp	Main Oil Differential Pressure
pfc	Air / Oil Heat Exchanger Valve Position
ptt2	Engine Inlet Total Temperature
ppt2s	Engine Inlet Total Pressure
pacwf	Fuel Flow
pn1	N1
pn2	N2
mach	Mach
palt2	Pressure Altitude (hp)
hdot	Altitude Rate
alpha	Angle of Attack
ptrasl	Thrust Lever Angle

Initially neural networks were considered for modeling the lubrication system data, however, due to computational burden in training these ANNs, simple linear models were considered. Those models took the form:

$$y(t) = c_1 u_1(t) + c_2 u_2(t) + \ldots + c_p u_p(t)$$

where $y(t)$ is the target variable at time t, $u_i(t)$ are the corresponding input variables, and c_i are the input weighting coefficients. There are p variables used as input to the model. The linear modeling problem is to estimate the c_i's given "training" data. It was found that linear models fit the lubrication data as well as the neural net models. To further reduce complexity, a model reduction process using a *backwards elimination* approach was applied to identify the *optimal* subset of input variables for both models (POILQ and PN4SP). This resulted in models with 7 input variables, albeit, different variables for each model. An example of the response for the Oil Quantity parameter versus the actual measured Oil Quantity is given in Figure 7.
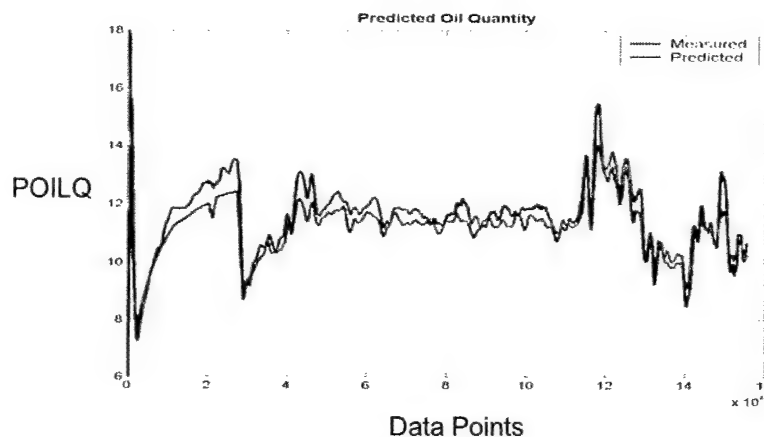

Figure 7: Measured versus Predicted Oil Quantity

Further detail can be found in [16].

Other Models and Algorithms

Models and algorithms used for processing the Inlet Debris and Engine Distress Monitors (IDMS/EDMS), Stress Wave sensor and vibration data are in their initial development (for the C17-T1 program) and will not be discussed in the present paper.

HIGH LEVEL FUSION

The principal objective of the High Level Fusion Module shown in Figure 1 is to transform multiple sources of engine health and performance information into a diagnosis/prognosis knowledge base. Embedded in this transformation process is a fundamental understanding of gas turbine system malfunctions, as well as a systematic methodology for inserting evidence to support a specific root cause of the malfunction. The information fusion occurs through an algorithm that attempts to combine the supporting evidence in order to optimize the utility of the diagnostic information. The term utility is used in the context of minimizing all diagnostic decision errors such as false alarms, missed detections, and incorrect malfunction isolation.

Diagnostic feature information available from the models and analysis algorithms discussed in the preceding section, along with engine and aircraft operational information may be considered as a whole in a high-level fusion module for the purposes of extracting an overall

engine health assessment. For the C17-T1 application we have envisioned two levels of information fusion. The first level accepts feature information and delivers an engine health assessment that feeds a second tier that also accepts maintainer and pilot observations and engine maintenance history information and returns a recommended maintenance action. Both of these high-level fusion processes are being developed within the C17 PHM Flight Test program and Data Fusion program and are currently in the initial modeling stage.

The second tier of information fusion described above consists primarily of a Failure Modes Effects and Criticality Analysis (FMECA) model of the F117 engine along with a line maintainers' Fault Isolation Manual (FIM) procedure. The mathematical vehicle for encapsulating this information is a Bayesian Belief Network (BBN) that consists of a collection of directed graphs with conditional probabilities linking the nodes of the graphs and a process of updating the conditional probabilities using Bayes Law [17] as information (observations) become available. Bayesian Belief Networks require accurate conditional probability information to initialize the network. In the present application, the FMECA analysis component reliability information is used to *seed* the process. A discussion of Bayesian Belief Networks is outside the scope of the present presentation but can be found in a number of references in the general literature [18,19].

The first level of information fusion deals with information of a more subjective nature for which precise conditional probabilities would be difficult to assess and assign and BBNs are known to be computationally burdensome. Unlike the second fusion tier that depends on a human interface to provide observational information, the primary level would operate in real time during flight. Thus, the BBN was not deemed to be an appropriate mathematical mechanism for accomplishing the information fusion at the primary level. A suitable alternative for the BBN that is more computationally tractable is the Fuzzy Belief Network (FBN) [20,21]. Like the BBN it uses a directed graph framework but uses fuzzy belief functions to assign a level of confidence in lieu of exact conditional probabilities. An in-depth description of the high-level fusion module FBN process is outside the scope of the present paper. It will suffice to say that the FBN construction is dictated by the particular engine data and analyzed features available within a given application and requires expert knowledge (and experience) to formulate the parametric inter-relationships and assignable fuzzy levels of confidence.

The advantage of first tier fusion can be appreciated by considering a hypothetical example scenario. Consider the output of the Gas Path Analysis (GPA) module described in the previous section that does not directly address measurement errors in the form of bias or drift. If, for example, a fault in the fuel flow measurement system were encountered resulting in a bias shift in fuel flow, the results of the Gas Path Analysis would be corrupted in that the shift would be interpreted as a combination of component performance shifts. However, as Figure 4 suggests, the Gas Path Anomaly Detector (AD) would likely perceive and flag the non-nominal condition, as well as returning an abnormally high Fuel Flow measurement distance metric. The combination of the GPA and the AD results would allow us to infer the Fuel Flow measurement error and effectively ignore the (erroneous) GPA performance excursions. Conversely, if there had been a component performance shift instead, (a FOD or DOD event, for example) then once again we would see performance changes in the GPA. In this case we would also likely see an AD fault flag accompanied by measurement distance metrics in more than just one parameter. This combination of GPA and AD results would allow us to infer that an *event* has occurred and that the reported GPA results can be taken with increased *confidence*. Clearly the inclusion of other sensor information and analysis features could further substantiate or refute a given hypothesis in terms of reported *confidence* level. Constructing the inter-relationships between sensor and feature information available across the disparate information sources, along with assigned *confidence* levels, is the challenge of the high-level fusion task.

SUMMARY

A pivotal requirement for successful diagnostics is the ability to detect and isolate engine system faults in a timely manner. Data Fusion provides for the integration of data or information from multiple sources, in order to enhance diagnostic visibility, increase diagnostic reliability and reduce the number of diagnostic false alarms.

In this paper we have discussed an approach to developing an information fusion system for aero gas turbine engines. A general architecture for an on-board data fusion system has been presented and examined which addresses a variety of potential data sources. A specific data fusion methodology that is being developed under a NASA C17-T1 PHM research program was presented covering data sources, signal processing, and some traditional and novel analysis modules for engine health feature extraction. A brief overview of a high-level fusion module framework was also given.

FUTURE WORK

Future work on this project will focus on the development of the Fuzzy Belief Network for combining feature information from the various analysis modules. Initially this will applied to the to gas path components as alluded to earlier and will be incrementally expanded to include other components and feature information.

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APPENDIX

Table A: Examples of Parameter Measurement Information for Data Fusion

Parameter	Sample Rate (Hz)	Engr. Units	Parameter	Sample Rate (Hz)	Engr. Units
Aircraft			**Gas Path**		
Mach No.	25		N1	20	% RPM
Pressure Altitude	25	FT	N2	20	% RPM
Calibrated Airspeed	25	KNOTS	Burner Static Pressure	5	PSIA
True Airspeed	25	KNOTS	High Pressure Compressor Exit Total Temperature	5	Deg C
Indicated Airspeed	25	KNOTS	EGT Total Temperature	20	Deg C
Angle of Attack	50	DEG	Engine Inlet Total Temperature	5	Deg C
Alpha Dot, (AOA Rate)	6	DPS	Engine Inlet Total Pressure	5	PSIA
Roll Angle	50	FPS	Low Pressure Turbine Exit Total Pressure	5	PSIA
Pitch Angle	50	FPS	Fuel Flow	5	PPH
Heading Angle	50	DEG	Low Pressure Compressor Exit Total Temperature	20	Deg C
Roll Rate	50	DPS	Low Pressure Compressor Exit Total Pressure	20	PSIA
Pitch Rate	50	DPS	**Structural Assessment Sensors**		
Yaw Rate	50	DPS	Stewart Hughes IDMS Sensor # 1	12.5K	VDC
Flight Path Angle	50	DEG	Stewart Hughes IDMS Sensor #2	12.5K	VDC
Altitude Rate	25	FPM	Stewart Hughes EDMS Sensor	12.5K	VDC
Total Temperature	10	Deg C	SwanTech Sensor #1 (Inlet Stator)	23.15K	VDC
Total Pressure	25	IN HG	SwanTech Sensor #2 (E-Flange)	23.15K	VDC
Static Temperature	10	Deg C	SwanTech Sensor #3 (Gearbox)	23.15K	VDC
Static Pressure	25	IN HG	SwanTech Sensor #4 (K-Flange)	23.15K	VDC
Commands			SwanTech Sensor #5 (#5 Bearing Oil Pressure)	23.15K	VDC
High Press. Compressor Variable Vane Position	5	Inches	B-Flange High Frequency Acceleration	46.3K	g
Station 2.5 Bleed Valve Position	5	% Open	B-Flange Low Frequency Acceleration	5.8K	g
Thrust Lever Angle	20	Degrees	P-Flange High Frequency Acceleration	23.15K	g
High Pressure Turbine Clearance Valve Position	5	% Open	P-Flange Low Frequency Acceleration	5.8K	g
Low Pressure Turbine Clearance Valve Position	5	% Open	Gearbox High Frequency Acceleration	46.3K	g
Air / Oil Heat Exchanger Valve Position	5	% Open	Gearbox Channel 1 (X-axis Acceleration)	23.15K	g
Oil/Fuel System			Gearbox Channel 2 (Y-axis Acceleration)	23.15K	g
Oil Quantity	2.5	Quarts	Gearbox Channel 3 (Z-axis Acceleration)	23.15K	g
Fuel Temperature at Fuel/Oil Heat Exchanger	5	Deg C			
Main Oil Temperature	5	Deg C			
Main Oil Differential Pressure	5	PSIG			
# 4 Bearing Compartment Exit Pressure	2.5	PSIG			
Fuel Pump Exit Pressure	20	PSIA			
#1, 2, 3 Bearing Compartment Exit Temperature	20	Deg C			